The Need for a Systems Perspective in Control Theory and Practice

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Introduction

Control systems have had a profound impact on society as theories, techniques, and algorithms have migrated from the laboratory to thousands of products. As the control community continues to improve its solutions, ideas are being generated for a new era of applications that are fundamentally different from their predecessors. Where applications once employed control systems for greater performance, new applications require control systems for their very existence. Examples of these types of systems are ultra-agile military aircraft, large-space-structure (LSS) observatories, and formation-flying spacecraft constellations. This *control-enabled* class of systems

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(also called "high-performance systems") is changing the role of control science in engineering.

Control theoreticians and practitioners have both enthusiastically accepted the challenge of controlling high-performance systems. The control theory community has focused on pushing the limits of controller design, seizing (and creating) new opportunities provided by more sophisticated mathematics, more efficient numerical algorithms, and increased computer speed. In doing so, control theoreticians have found ways to incorporate more knowledge about what we know and do not know about the system into controller design. Elegant optimal control theory has been developed to design controllers that use minimum fuel or get us from here to there in minimum time. Estimation theory has shown us how to extract useful signals from corrupted signals. Robust control theory has been developed that allows us to describe system uncertainty mathematically, then allows us to incorporate this description into control analysis-synthesis methods. Adaptive control , system identification , and intelligent control have shown us how to obtain and then use new knowledge of our systems for controller synthesis.

Even while continuing to be students of new control theory, many practicing control engineers are coming to a sobering realization. When high-performance systems demand strict performance requirements, no control theory *in itself* may be satisfactory. In these cases, a new analysis-synthesis framework must be employed. Systems must be analyzed from end to end to understand how both the systems themselves, as well as their controllers, may be modified to realize the ultimate objectives of their application.

As a result, although traditional control theory continues to focus much research on better controller design, practicing control engineers are being forced to broaden their perspective. They are being asked to analyze all factors within *control-enabled* systems that can ultimately affect performance. These factors clearly include controller design as a central component but, depending on the application, structures, optics, signal processing, fault detection, and computer processing may also fall into the control engineer's consciousness.

Fortunately, control practitioners are finding themselves analytically well equipped for high-performance systems analysis with theoretical machinery adapted from controller design methods. However, the control theory community has not yet focused attention on systems-control analysis-synthesis as a discipline. (For lack of a short name for systems-control analysis-synthesis, we will abbreviate it herein as SCAS.) Understanding this evolving gap between control theory and the needs of control practitioners can lead to some very positive results. These include new research directions, a broadening influence of control theory on other engineering disciplines, and the solution to more and more complex multidisciplinary problems.

In this article, we examine the new role of control science in high-performance systems and its implication for control theory. In the next section, we describe the traditionally "serial" role of control science in systems design and the evolving iterative system-control design process used for high-performance systems. Next, we discuss several high-performance systems that use this iterative design process. Then, we describe past work that is related to SCAS, followed by an examination of fundamental control theory concepts that may be extended as part of an SCAS theory.

Finally, we present conclusions.

From Serial to Iterative Design

Control theorists primarily study the analysis-synthesis of controllers within a serial framework as illustrated in Fig. 1. Traditionally, application-specific engineers

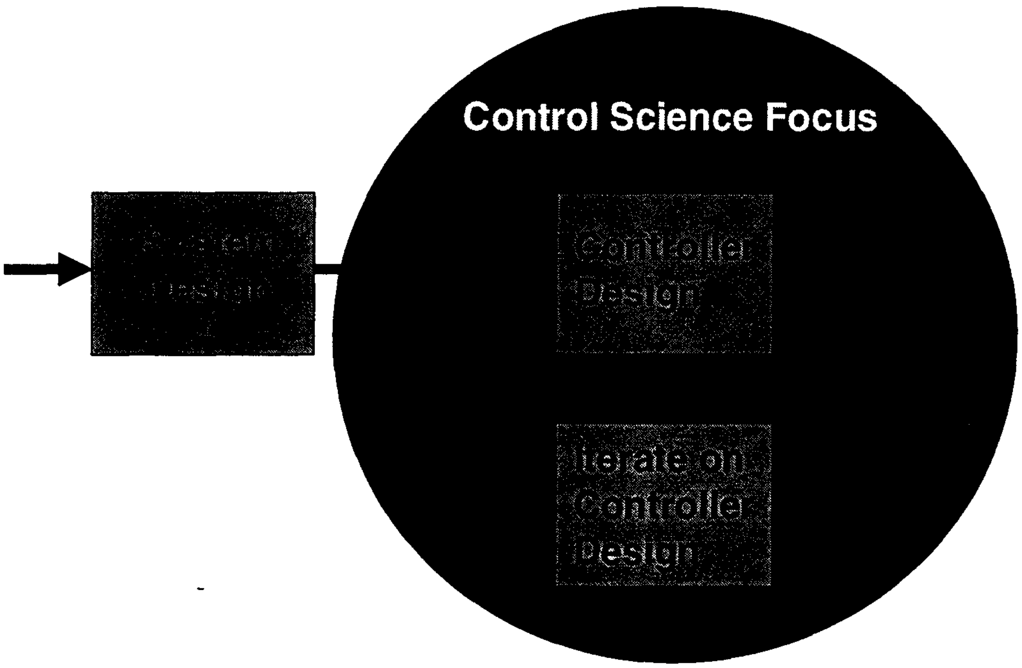

Figure 1: Serial analysis-synthesis approach.

have designed systems. Once they have completed the design, they have passed two products to the control engineers: (1) the system itself and (2) physical requirements that the system must achieve after control design. The control engineer may then model the system within a specific mathematical framework, measure inputs and outputs, and possibly even poke and prod the system to learn how it behaves. At the same time, physical control requirements are translated into the language of control theory (gain margin, rise time, quadratic cost, infinity-norm, etc.). The control engineers then apply the best control theory they know for the particular application. After several iterations and juggling of fundamental trade-offs (performance vs. robustness, etc.), they hopefully achieve sought-after performance.

As engineers have passed new classes of systems to control researchers, new control theory has developed. For example, the need for understanding locomotive steam engines and centrifugal governors led to linear stability analysis [1]. The use of feedback amplifiers in new electrical circuitry led to classical control theory [2]. The need to guide and track space vehicles helped push the formulation of state-space theory and optimal control and estimation [3]. Lightly damped space structures led to distributed parameter control methods [4]. The ever increasing complexity and accompanying uncertainty in MIMO systems led to $\mathcal{H}_\infty$, μ-synthesis, and other robust methods. Complex systems in which models are hard to quantify led to fuzzy [5] and neural control [6].

On the other hand, the serial design approach has led to some unfortunate consequences. First, the "last step control" approach has limited the role and influence of control science. Most non control engineers perceive controls science as esoteric and non-intuitive. Therefore, ideas and techniques invented or perfected by the control community have a hard time affecting non-controls disciples. Second and perhaps more important for control science, the serial design approach is sure to fail as systems demand greater and greater performance. In these cases, control engineers must work within the system design framework to help develop systems and controllers that will *allow* requirements to be met.

The alternative to the serial approach is iterative system-controller analysis-synthesis. Once an initial system design is completed, control analysis is conducted using software models and tailored hardware experiments. This analysis leads to possible control and/or system modifications needed to make the system feasible. Once a feasible system and controller solution is demonstrated, additional changes that may optimize the design are evaluated. This process continues until the design space stabilizes. This alternative analysis-synthesis approach is illustrated in Fig. 2.

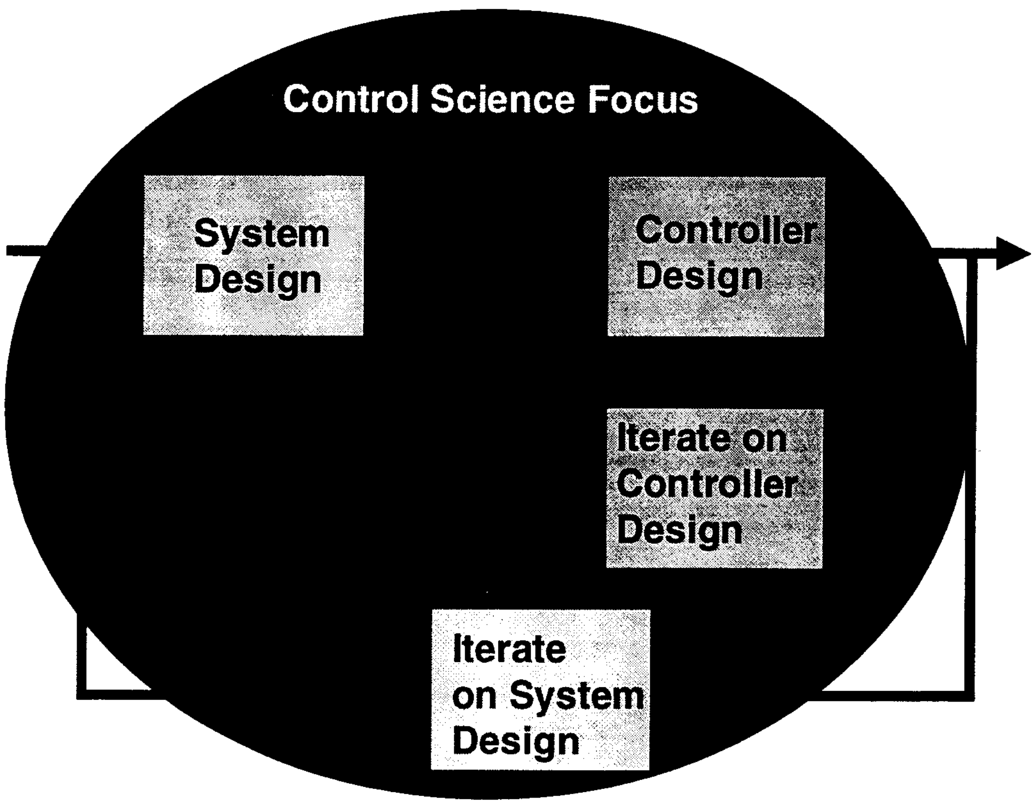

Figure 2: Iterative analysis-synthesis approach.

This iterative framework requires control engineers to be involved early in the design phase of systems, to give input into how a particular system design may affect controller design and vice versa. It is only early in the design phase that major changes can be made. System-controller trades require a thorough knowledge of control options, from Bode feedback design to modern time-domain techniques, as well as the mathematical background underlying these methods, but they also require the control engineer to know much more than controller design. Control engineers must have in-depth knowledge of specific applications. Important dynamics, hardware limitations, actuator and sensor options, and computing power all affect the ability to meet strict requirements.

The iterative framework also requires control engineers to be able to develop, use, and interpret results from tools such as multidisciplinary simulation and specialized hardware testing. Knowledge of general principles of mathematical modeling, including the strengths and weaknesses of numerical methods, allows control engineers to ascertain the effects of system and control changes on overall performance. Eventually, possible solutions must be tested in actual hardware to validate simulation results; however, these hardware tests are rarely done using a full-up system. Rather, a specific test setup is designed to validate a particular solution or concept. Control engineers must help design these experiments so as to instill confidence that a demonstration on a specialized testbed will translate to the actual system once it is built.

Aerospace Systems

Voyager

Spacecraft engineers realized the importance of concurrent SCAS with the advent of flexible space structures. Unlike rigid spacecraft, flexible space structures embody dynamics that help disturbances propagate over the entire spacecraft. As a result, all subsystems on such a spacecraft are dynamically connected. In addition, closed-loop control changes the way these dynamics manifest themselves. This is known as control structure interaction. An early example of this interaction was on the NASA Voyager spacecraft (1977) shown in Fig. 3. A controlled scan platform was mounted on the tip of a 2.3-m boom. To operate correctly, both the platform controller and the boom had to be designed concurrently. Control engineers designed the platform controller and simulated the spacecraft, boom, and platform in closed loop. Based on these simulations, the control engineers modified the controllers and suggested boom alterations to the boom designers.

SIM

Individual flexible structures on spacecraft (such as those on Voyager) led to spacecraft concepts that were dominated by large flexible space structures (LSS). Motivated by large flexible space structure work, new space observatories envisioned for early in the next century will require unprecedented control performance for instruments placed on top of these LSS. Optical elements on these large space observatories must be stable to within a single wavelength of light!

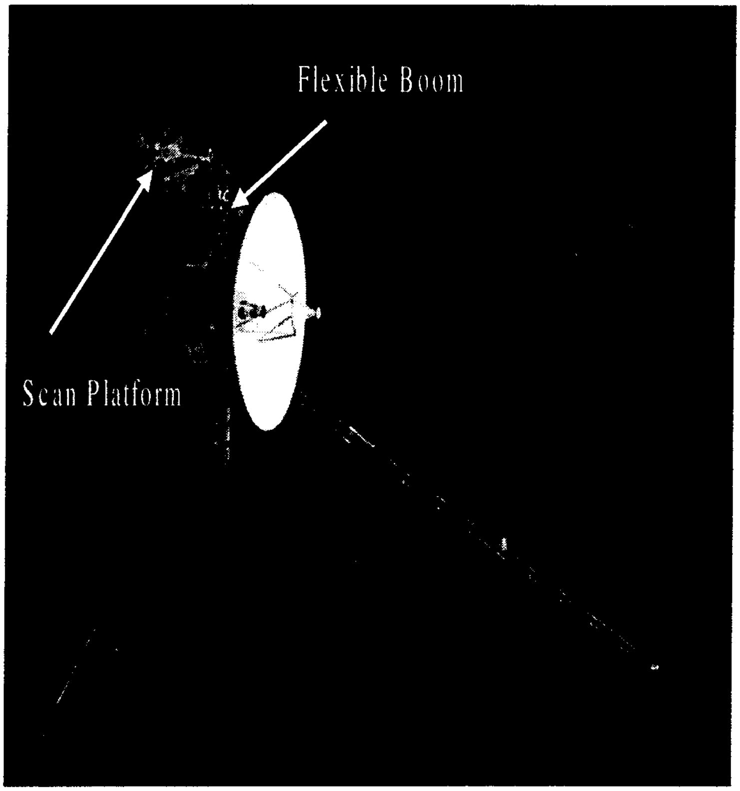

Figure 3: The Voyager spacecraft.

Consider NASA's Space Interferometry Mission (SIM) shown in Fig. 4. Currently under development at the Jet Propulsion Laboratory, TRW, and Lockheed Martin, SIM is one of a new generation of space observatories that will use optical interferometry to synthesize large optics using only a series of small optics. SIM consists of a series of telescopes and other optical elements placed on top of a flexible 10-m space structure. By physically moving the telescopes within a two-dimensional surface in space, the observatory will partially mimic the science return of a single 10-meter optic; however, to employ required signal processing techniques, individual optics on the structure must maintain relative positions and orientations to within nanometers (1e-9 meters). This extremely stringent requirement must be met in the

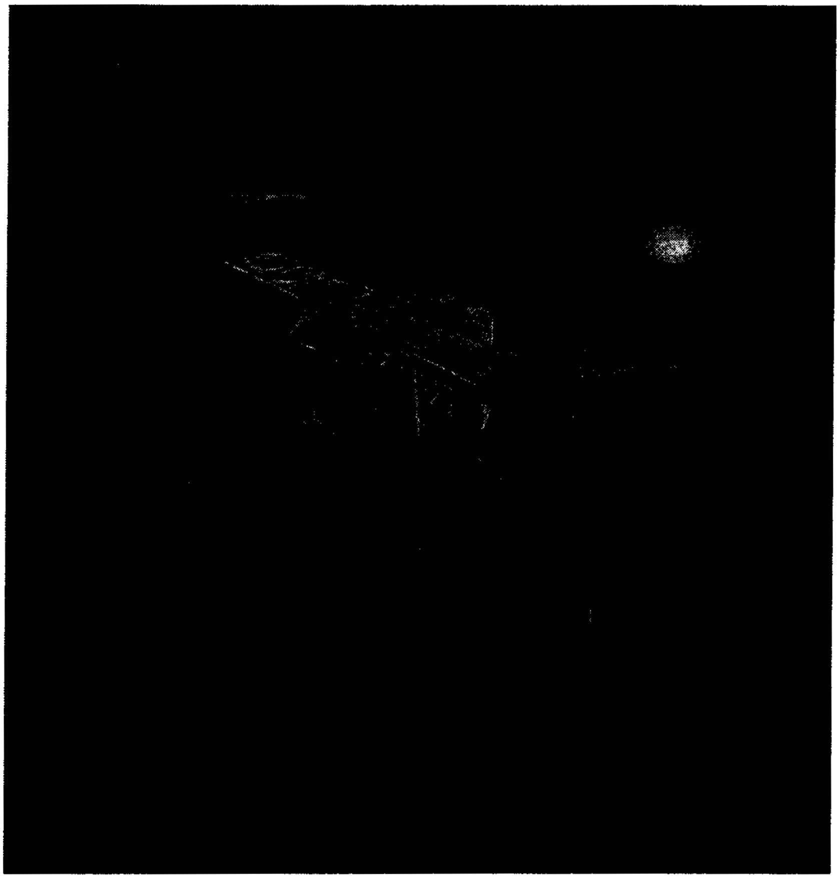

Figure 4: One possible design for the Space Interferometry Mission.

face of disturbances from attitude control actuators, thermal gradients, solar pressure, microdynamic structural snaps, and other disturbance sources. As is typical for high-performance aerospace systems, iterative SCAS is crucial for SIM. First, it is not clear initially that there *exists* a control method that can meet the system's requirements. Second, due to its high cost, the design cannot benefit from trial-and-error experience of large-scale production.

As a specific example of how iterative SCAS is being used for SIM, consider the problem of optics stabilization in the presence of reaction wheel disturbances. Reaction wheels are momentum exchange devices used to point spacecraft and maintain attitude. As a reaction wheel spins slower or faster, it not only produces the torque necessary for spacecraft pointing, but it also imparts unwanted disturbances into the system due to imbalances and friction within the reaction wheel mechanism. For most spacecraft missions, these disturbances are negligible to mission success; however, this is not the case for interferometers. Due to ultra-stringent performance requirements, even small disturbances can be devastating to the mission. Reaction wheel vibration attenuation is generally believed to require three complementary vibration control strategies (Fig. 5): (1) active or passive reaction wheel isolation, (2) active or passive structural quieting, and (3) active control of optics. Clearly, the design of controllers for each of these elements fundamentally impacts the overall system design.

As mentioned previously, the first goal of iterative SCAS is to prove the existence of a solution. This is done for SIM using a combination of simulation and specialized hardware testing. The key tool for simulation study is a multidisciplinary model of the proposed interferometer (Fig. 6). This model consists of a structural finite-element model, a linear optics model, and a control model all tied together within a common software framework. These models make it possible to quantitatively predict the effect of mechanical disturbances on *optical* performance metrics in both open and closed-loop configurations. The major testbed for vibration study (shown in Fig. 7) contains all necessary systems to perform space-based astrometric measurement [7]. Using this testbed, proposed vibration attenuation solutions can be physically implemented in hardware. Once a solution is demonstrated in both software and hardware, control engineers can work collaboratively with optics and structures engineers to op-

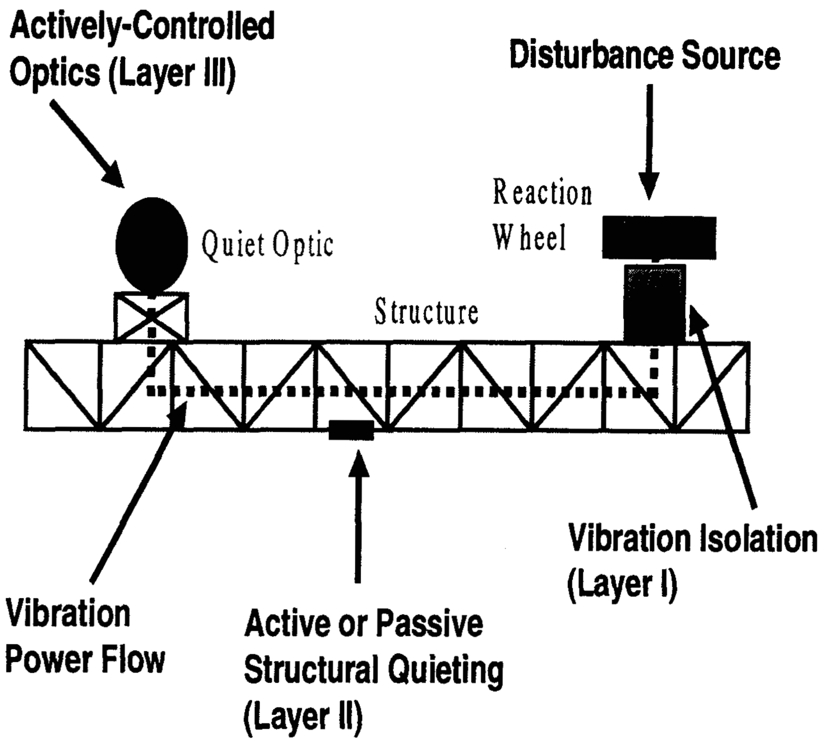

Figure 5: Vibration control strategy for SIM.

timize the design using a variety of control laws, sensors and actuators, structural configurations and materials, and/or optical designs [8].

Other Upcoming Control-Enabled Aerospace Systems

Structurally connected optical interferometers are only one class of systems in which iterative SCAS is needed. In the future, optical interferometer observatories will be constructed without any structure connecting them. Instead, they will use a coordinated fleet of spacecraft flying in precision formation. Controllers will monitor the position and attitude of each spacecraft and keep the ensemble working as one

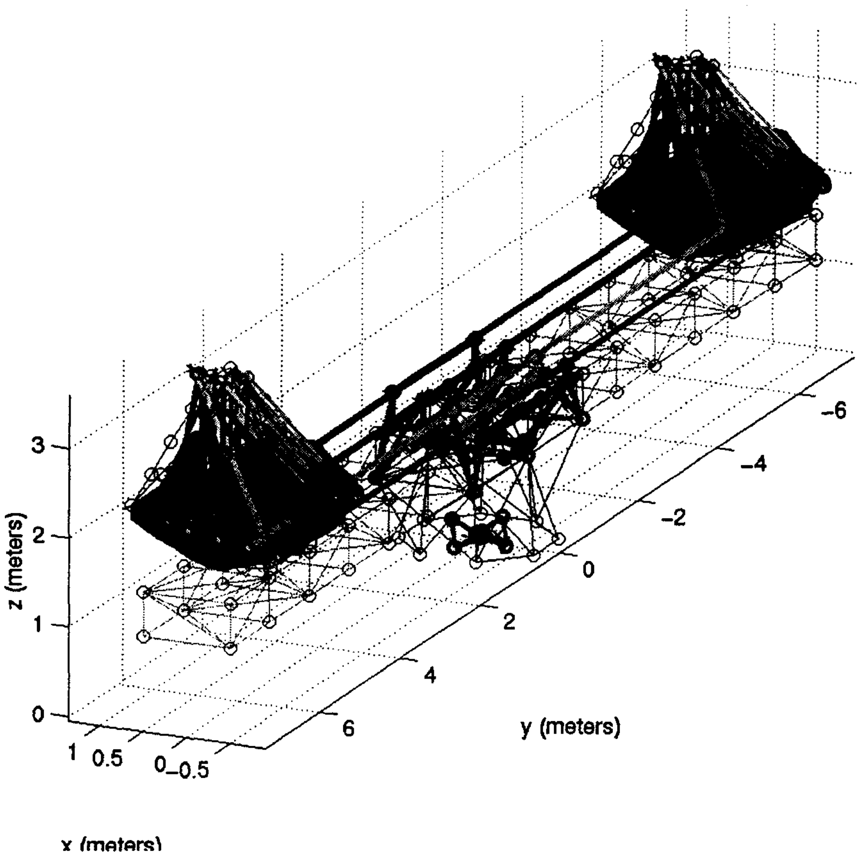

Figure 6: SIM integrated controls/structure/optics model.

unit, as if they were very rigidly connected. One such mission, Terrestrial Planet Finder, is shown in-Fig. 8. Its mission will be to directly detect Earth-like planets in other solar systems. The multiple-agent framework is currently being studied for a wide variety of other control-enabled aerospace applications. These applications include formation flying high-altitude aircraft for communication networks [9] and formation coordination of robots for Mars exploration [10] (Fig. 9). This article focuses on aerospace applications; however, important challenges are sure to come from additional non-aerospace applications such as semiconductor manufacturing, chemical processing, and biomedical engineering.

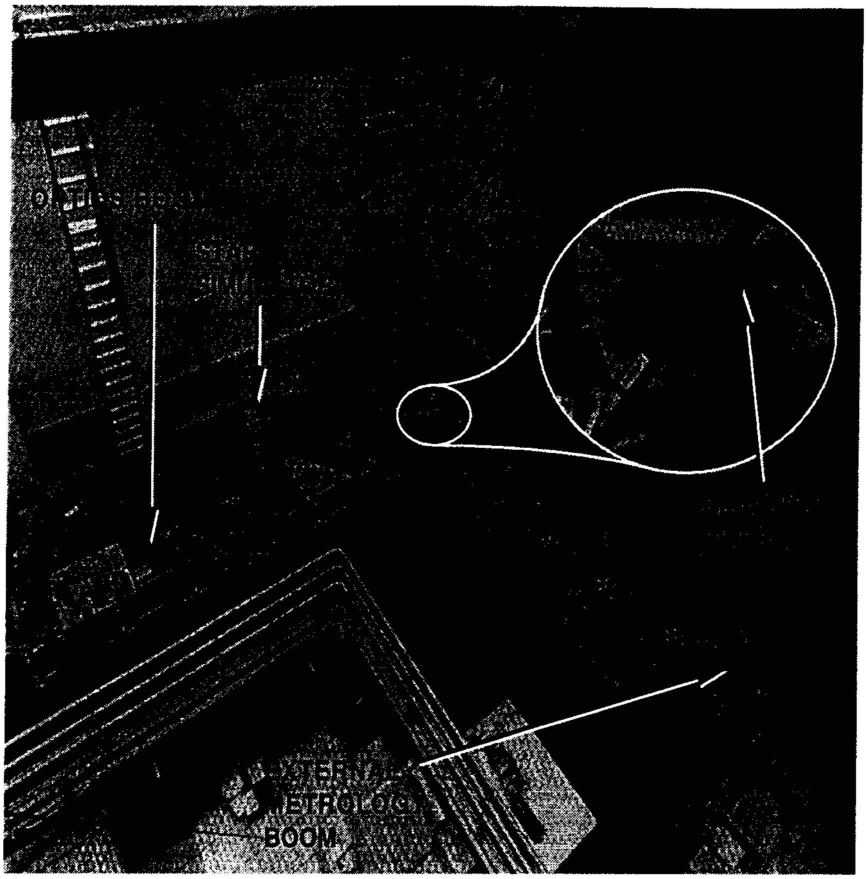

Figure 7: Vibration study testbed for the Space Interferometry Mission. Vibration control strategies and hardware are demonstrated on this testbed as proof that nanometer stability requirements can be met.

Past Research

The control theory community has yet to embrace SCAS as a unified discipline, such as robust control theory or system identification theory. However, past research motivated by emerging applications is leading toward such a discipline. The following is not meant to be a comprehensive review, but rather to give an idea of work related to an SCAS discipline.

Figure 8: One concept for Terrestrial Planet Finder.

Large space structures tend to have closely packed, lightly damped modes that start appearing at very low frequencies. This can lead to instabilities in controlled structures, as the bandwidth of the controllers often overlaps several structural modes. Distributed-parameter models (partial-differential equations) best describe large space structures. These partial-differential models are not well suited for traditional finite-order controller design. Therefore, finite-order models often approximate partial-differential models. These finite-order models are then used for controller analysis-synthesis. The resulting reduced-order controllers are applied to the actual (infinite-dimensional) system. Controllers designed based on reduced-order models affect not only the modes in the reduced-order model, but also modes that are not in the model. These previously stable, unmodeled modes can suddenly become unstable in the presence of control, a problem known as spillover. The theoretical issues associated with all of these problems drew much attention in the 1980s and early 1990s. From these efforts came a host of new theories and algorithms in the areas of distributed-parameter control, spillover reduction and accommodation, model reduction, sensor and actuator placement, frequency shaping, positivity and modal control, among others. Good

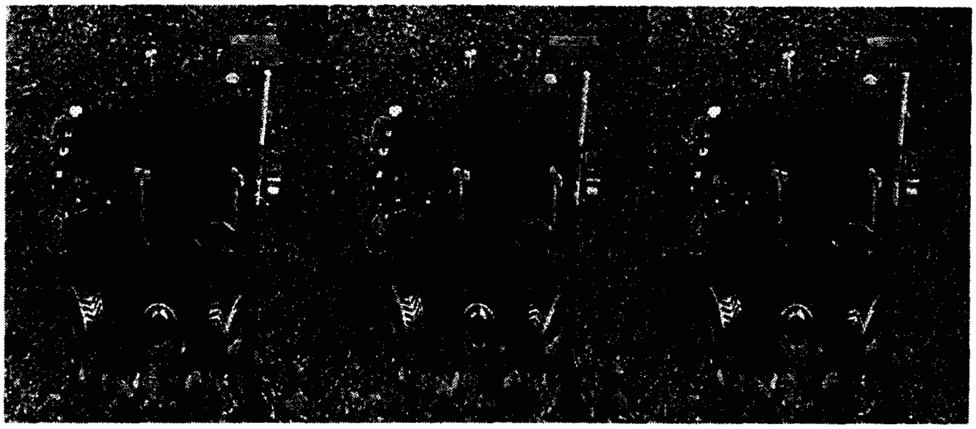

Figure 9: Robot teams working in a coordinated manner may help search for life on other planets.

reviews of the field are given in Meirovitch [11] and Joshi (S.M.) [12].

Control-structure interaction problems highlighted to researchers that system identification, reduced-order modeling, and controller designs are not independent problems. For example, as described in Skelton and Hu [13], reduced-order models for controller design cannot be constructed without knowledge of which inputs the model must propagate. Unfortunately, these inputs are exactly the control for which the model is needed in the first place. Iterative methods for modeling and control are discussed in Skelton and Hu [13], Liu and Skelton [14], and Zhu and Skelton [15]. Similarly, system identification and robust control were recognized to be complementary problems. A good series of papers on this subject is given in Kosut et al. [16]. One iterative approach to system identification and robust controller design is given by Bayard et al. [17], who developed an alternating curve-fitting and control design procedure to produce a series of controllers that have monotonically improving robust performance.

Control-structure interaction also motivated a few researchers to think about how both structures and controllers could be designed concurrently. Meirovitch [11] contains a good expanded list of researchers who have worked in this field (prior to 1990). Hale et al. [18] considered the problem of optimal structure-control force design using a scalar cost functional for maneuvering a flexible space structure from specified initial condition to specified final condition in a given amount of time. Miller and Shim [19] considered the problem of combined structural mass/control-energy optimization for reducing mass and suppressing vibrations using gradient-based search methods. Lim and Junkins [20] considered robustness optimization of control-structure design. They optimized total mass, stability robustness, and eigenvalue sensitivity with respect to structural parameters, control parameters, and actuator locations. Maghami et al. [21] studied the combined control-structure design using dissipative controllers. Smith et al. [22] and Grigoriadis et al. [23] approached the problem in a different way. They assumed that an active controller has been designed a priori that meets performance specifications. They then go on to change the active controller, as well as redesign the structure, to reproduce the performance of the original controller and structure, only now with less control power.

One of the first communities to understand that systems and controllers must be analyzed and synthesized concurrently was the military aircraft industry. Many high-performance aircraft are designed open-loop *unstable* for extreme agility. As such, these aircraft are extremely dependent on their controllers. Furthermore, every design decision, from choice of body materials to aircraft shape, closely interacts with control design. In the past 10 years, the aircraft design community has led the new field of multidisciplinary design optimization (MDO) [28]. MDO aims to explore the interactions between structures, aerodynamics, flight mechanics, thermal dynamics, and controls by developing analysis tools in a common software framework. NASA Langley's Division of Multidisciplinary Optimization [24] defines MDO theory as composed of mathematical modeling, approximation theory, computational tradeoff theory, smart reanalysis, sensitivity theory, and optimization theory. MDO mathematical modeling aims to create suites of disciplinary models that can be integrated into a single environment. Approximation research [25] aims to be able to construct system performance using the minimum amount of needed information from each discipline. Computational tradeoff aims to understand the relationship between computation cost and accuracy in multidisciplinary simulation tools. Smart reanalysis aims to reduce the computational load of analysis using multidisciplinary simulation. Sensitivity theory [26] allows the mathematical representation of the effect of a change in a parameter in one field on a parameter in another field (e.g. wing shape on material selection). Finally, optimization theory [27] aims to find efficient ways to decompose, search, and optimize over very large design spaces. A good series of articles in this field is given in Livne [28]. Although often mentioned as a vital component of MDO, control theory has not been well connected to the MDO community. This disconnect, as well as the quickly growing complexity of the problems, has usually limited MDO studies involving control to simple PID controllers. Recently, Masters and Crawley [29] studied evolutionary design of controlled structures using genetic algorithms to tune structural parameters, controller parameters, and sensor and actuator locations. Guttierrez [30] combined disturbance, uncertainty, and sensitivity analysis, as well as integrated modeling, to show how to better design controlled high precision structures.

Finally, a number of other areas have been studied. To make control systems truly robust, failures must be accurately and swiftly detected, isolated, and accommodated. This has led to failure detection and isolation (FDI) theory [31]. Estimation theory, multiple hypothesis testing, parameter estimation, and analytical redundancy have all been proposed as methods for fault detection and isolation. Most of these methods have been developed from control-estimation theory. Optimal sensor/actuator placement can have a large impact on control performance (e.g., [32]). In addition, computational realities such as finite word lengths and round-off error can significantly affect controller performance. Efforts to a priori account for these effects in design of optimal controllers and estimators have been studied by Moroney et al. [33] and Liu et al. [34]. Lu and Skelton [35] studied design economics by considering the combined optimization of control laws and instrument selection. They assume that instrument cost is directly related to signal-to-noise measures of the instruments.

Fundamental Control Theory Concepts

At present, most practiced SCAS is done ad hoc by iterating between design and control until a suitable solution is found. Guiding analytical tools and design algorithms to aid designers specializing in varied multidisciplinary applications would be very helpful to converge to suitable designs more quickly. As partially shown by the studies of the last section, we may exploit fundamental control theory concepts toward such design tools. These concepts include sensitivity, uncertainty, robustness, and optimality.

Sensitivity

One of the first theoretical contributions of control theory was the realization that feedback leads to sensitivity reduction [2]. This concept is also extremely important in SCAS. Sensitivity analysis is already being explored in multidisciplinary design (without controllers). However, the addition of feedback controllers changes the problem. Performance must not be radically altered by system variations due to structural uncertainty, environmental disturbances, material property changes, sensor and actuation degradation, and so on. It is unclear, however, if this desensitizing is best achieved through change of plant design or increased control authority. The extension of sensitivity theory to include both systems design and controller design options could be fruitful.

Uncertainty

The need to capture uncertainty in systems has played a large role in control theory. Uncertainty also affects systems design. For example, in critical early phases of project design, multidisciplinary models are the only design tools available; however, performance predictions using multidisciplinary models are always somewhat uncertain due to several factors, including component uncertainties, model reduction, and discretization. As a result of these uncertainties, overall system designers tend to "overdesign" subsystems to account for uncertainty. For example, optics are made smoother than necessary, materials are made stronger than necessary, and sensors are made less-noisy than necessary. This conservatism also leads to overly expensive systems. Control theory has a similar situation. Control engineers must trade off controller performance for uncertainty robustness. If uncertainty is overestimated, resulting controllers cannot meet as strict performance targets as would otherwise be possible. How to best describe plant uncertainty and its effect on control synthesis is still an active area of research in the control theory community. Continued study of how to systematically account for individual subsystem uncertainty into combined system/controller design would be very useful.

Robustness

Using the concepts of sensitivity and uncertainty, robust controller theory has been developed. "Robust" controllers guarantee stability and/or performance for admissible perturbations within a predefined set. This concept could be extended to SCAS.

Consider the diagram shown in Fig. 10. In the center is a nominal system design or "plant," P. Robust control theory deals with representing uncertainty, Δ, and then using this representation to design a robust controller, K. Incorporating system design options adds a new degree of freedom, represented as δP. The combination of nominal plant, P, and a set of design changes, δP, results in a new generalized plant. Note that δP can be continuous (e.g., structural plant with continuously varying material damping) or discrete (e.g. design option 1 or design option 2). The

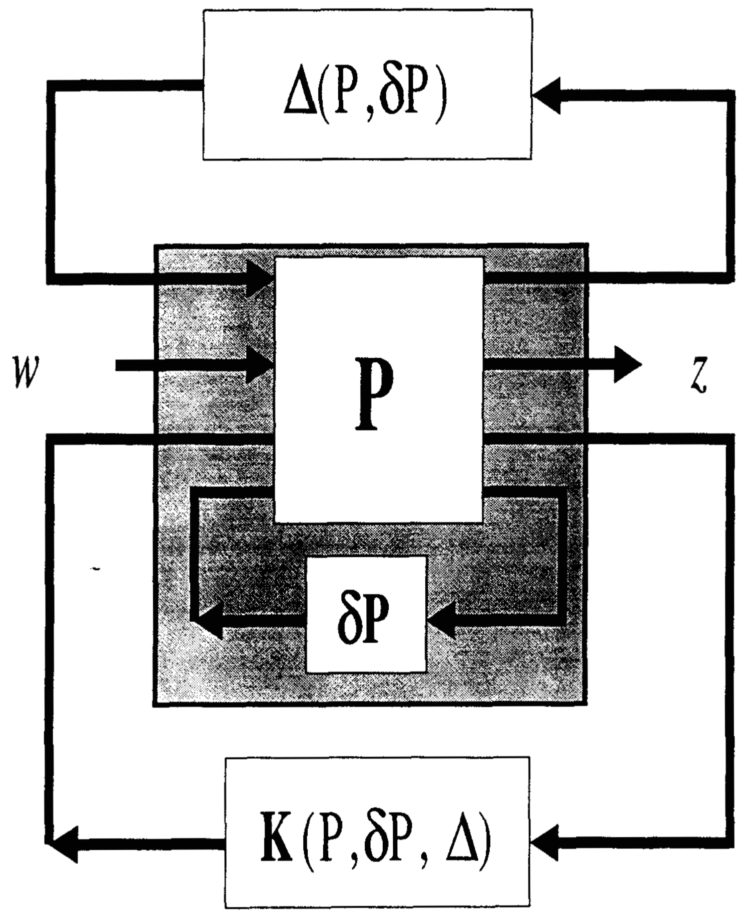

Figure 10: Modified version of traditional robust control diagram.

choice of δP has repercussions on both uncertainty modeling and controller design.

For example, one system design (δP_1) may lead to a class of uncertainties, $\Delta_1(P, \delta P_1)$, whereas another design may lead to another class of uncertainties, $\Delta_2(P, \delta P_2)$. The specific uncertainty set then affects the design of a controller. This is indicated as $K_1(P, \delta P_1, \Delta_1)$ or $K_2(P, \delta P_2, \Delta_2)$. Even without the plant design choices, δP, robust controller design is a difficult problem; however, the ability to develop systems that guarantee specific uncertainty classes may lead to a combined system-controller that can guarantee overall system robustness.

Optimality

Both the notion of optimality and methods of optimization have played central roles in control theory. Optimality is only defined with respect to a performance metric. In control theory, we use a number of metrics (e.g., $\mathcal{H}_2$, $\mathcal{H}_\infty$, and $\mathcal{L}_1$ norms). Systems design must also be optimal with respect to a defined performance metric. Heterogeneous subsystem metrics may have to be aggregated to an overall system metric. Alternatively, gross system metrics may need to be evaluated at the subsystem level. Development and understanding of meaningful metrics and their use in SCAS will be very important.

Optimization and control theory have been tied together with the influence of calculus of variations, dynamic programming, linear and nonlinear programming, and linear matrix inequalities (LMI). New optimization theory will be important to SCAS. Simultaneous plant/controller design problems many times lead to complex constrained optimization problems. Solutions are required for these problems that are both efficient and reliable. Of course, we should *not* aim to include every possible interaction from every possible discipline. Indeed, meaningful and tractable problem formulations will be important contributions to an SCAS discipline in themselves.

Conclusion

As systems demand greater and greater performance, control science takes on much more importance within system design. Rather than being enhanced by control, new systems are *enabled* by control systems. Practicing control engineers are being asked to evaluate not only controller changes but also system changes that can influence ultimate performance. As a result, theory and tools for integrated SCAS would be very helpful. Control science needs to broaden its perspective and see itself as an integral part of overall systems design. It is hoped that this article will help this reorientation process.

Finally, in keeping with the topic of this special section "Bridging the Gap Between the Theory and Practice of Control," this article focused on the implications of system-controller analysis-synthesis on control theory. In addition, the changing role of control science also has broad implications for control education, the definition of control science, and the relation between control science and other disciplines. It is also important for the control community to continue to address these issues.

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References

[1] J.C. Maxwell, "On Governors," *Philosophical Magazine*, vol. 35, pp. 385-398, 1868.

[2] G.F. Franklin, J.D. Powell, and A. Emani-Naeini, *Feedback Control of Dynamic Systems,* Reading, MA, Addison-Wesley, 1994.

[3] A.E. Bryson, *Applied Optimal Control: Optimization, Estimation, and Control,* New York, Taylor and Francis, 1981.

[4] V.B. Marks and C.R. Keckler, *NASA Workshop on Distributed Parameter Modeling and Control of Flexible Aerospace Systems,* Pasadena, NASA Conference Publication 3242, 1994.

[5] L.X. Wang, *A Course in Fuzzy Logic and Control,* Englewood Cliffs , NJ, Prentice Hall, 1997.

[6] B. Kosko, *Neural Networks and Fuzzy Systems*, Englewood Cliffs, NJ, Prentice-Hall, 1992.

[7] G.W. Neat, J.W. Melody, and B. Lurie, "Vibration Attenuation Approach for Spaceborne Optical Interferometers," *IEEE Transactions on Control System Technology*, vol.6, No. 6, pp. 689-700, 1998.

[8] S.S. Joshi, "Optimal Damper Placement for Spaceborne Interferometers Using H-Infinity Norm Optimization," submitted to *American Controls Conference*, Chicago, 2000.

[9] J.D. Wolfe, D.S. Chichka, and J.L. Speyer, "Decentralized Controllers for Unmanned Aerial Vehicle Formation Flight," Proceedings of the AIAA Guidance, Control, and Navigation Conference, San Diego, CA, AIAA Paper 96-3833, 1996.

[10] S.S. Joshi, "Towards Autonomous Robot Formation Control for Planetary Exploration," submitted to *IEEE Conference on Robotics and Automation*, San Francisco, 2000.

[11] L. Meirovitch, *Dynamics and Control of Structures*, New York, Wiley and Sons, 1990.

[12] S.M. Joshi, *Control of Large Flexible Spacecraft*, New York, Springer-Verlag, 1989.

[13] R.E. Skelton and A. Hu, "Modeling Structures for Control Design," *Computers and Structures*, vol.20, pp. 303-309, no. 1-3, 1985.

[14] K. Liu and R.E. Skelton, "Integrated Modeling and Controller Design with Application to Flexible Structure Control," *Automatica*, vol.29, no. 5, pp. 1291-1314, 1993.

[15] G.M. Zhu and R.E. Skelton, "Integrated Modeling and Control for the Large Spacecraft Control Laboratory Experiment Facility," *Journal of Guidance, Control, and Dynamics*, vol.17, no.3, pp. 442-450, 1994.

[16] R.L. Kosut, G.C. Goodwin, and M.P. Polis (Guest Editors), "Special Issue on System Identification for Robust Control Design- Introduction," *IEEE Transactions on Automatic Control* , vol.37, no. 7, 1992.

[17] D.S. Bayard, Y. Yam, and E. Mettler, "A Criterion for Joint Optimization of Identification and Robust Control," *IEEE Transactions on Automatic Control* , vol.37, no. 7, pp. 986-991, 1992.

[18] A.L. Hale, R.J. Lisowski, and W.E. Dahl, "Optimal Simultaneous Structural and Control Design of Maneuvering Flexible Spacecraft," *Journal of Guidance, Control, and Dynamics*, vol.8, no.1, pp. 86-93, 1985.

[19] D.F. Miller and J. Shim, "Gradient-Based Combined Structural and Control Optimization,"- *Journal of Guidance, Control, and Dynamics*, vol. 10, no. 3, pp. 291-298, 1987.

[20] K.B. Lim and J.L. Junkins, "Robustness Optimization of Structural and Control Parameters," *Journal of Guidance, Control, and Dynamics*, vol. 12, no. 1, pp. 89-96, 1989.

[21] P.G. Maghani, S.M. Joshi, and D.B. Price, "Integrated Controls-Structures Design Methodology for Flexible Spacecraft," *Journal of Spacecraft and Rockets*, vol. 32, no. 5, pp. 839-844, 1995.

[22] M.J. Smith, K.M. Grigoriadis, and R.E. Skelton, "Optimal Mix of Passive and Active Control in Structures," *Journal of Guidance, Control, and Dynamics*, vol.15, no.4, pp. 912-919, 1992.

[23] K.M. Grigoriadis, G. Zhu, and R.E. Skelton, "Optimal Redesign of Linear Systems," *Journal of Dynamic Systems Measurement and Control- Transactions of the ASME*, vol.118, no.3, pp. 598-605, 1996.

[24] Internet Web Site : "http://fmad-www.larc.nasa.gov/mdob/MDOB/", 1999.

[25] J.J. Korte, J. Dunn, A. Salas, N. Alexandrov, W. Follett, and G. Orient,"Multidisciplinary Approach to Linear Aerospike Nozzle Optimization," 33rd Joint Propulsion Conference, AIAA Paper 97-3374, Seattle, 1997.

[26] R.T. Biedron, J.S. Samareh, and L.L. Green,"Parallel Computation of Sensitivity Derivatives with Application to Aerodynamic Optimization of a Wing," *NASA Ames Computational Aerosciences Workshop*, August 1998.

[27] N. Alexandrov, "Multilevel Methods for Optimal Design," *Encyclopedia of Optimization*, (Edited by Floudas, C.A., and Pardalos, P.M.), Amsterdam, Kluwer Academic Publishers, in press.

[28] E. Livne (Guest Editor), "Special Issue on Multidisciplinary Design Optimization," *AIAA Journal of Aircraft*, vol. 36, no. 1, 1999.

[29] B.P. Masters and E.F. Crawley, "Evolutionary Design of Controlled Structures," *AIAA Journal of Aircraft*, vol. 36, no. 1, pp. 209-217, 1999.

[30] H. Guttierrez, *Performance Assessment and Enhancement of Precision Controlled Structures During Conceptual Design*, PhD Dissertation, Cambridge, Department of Aeronautics and Astronautics, MIT, 1999.

[31] R. Patton, P. Frank, and R. Clark, *Fault Diagnosis in Dynamic Systems: Theory and Application,* New York, Prentice Hall, 1989.

[32] S. Hakim and M.B. Fuchs, "Quasistatic Optimal Actuator Placement with Minimum Worst Case Distortion Criterion," *AIAA Journal*, vol. 34, no. 7, pp. 1505-1511, 1996.

[33] P. Moroney, A. Willskey, and P. Houpt, "Round-off Noise and Scaling in the Digital Implementation of Control Compensators," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 31, pp. 1464-1477, 1983.

[34] K.T. Liu, R.E. Skelton, and K. Grigoriadis, "Optimal Controllers for Finite Word-Length Implementation," *IEEE Transactions on Automatic Control*, vol. 37, no. 9, pp. 1294-1304, 1992.

[35] J.B. Lu and R.E. Skelton, "Integrated Instrumentation and Control Design," *International Journal of Control*, vol. 72, no. 9, pp. 799-814, 1999.